Numerical Weather Prediction

The Impact of Seawinds Scatterometer Data on Met Office Global Model Analyses and Forecasts.

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Abstract

Observations from spaceborne scatterometers contain information on the near-surface wind field and so make an important contribution to analyses for numerical weather prediction (NWP), particularly in areas where in situ measurements are sparse, such as the Southern Ocean. Recently observations have become available from the Seawinds instrument, initially from the *QuikSCAT* mission. This instrument has a wider swath width than earlier scatterometer designs and so offers increased coverage of oceanic winds making them of more interest to NWP centres. In this paper we describe the method used at the Met Office for using Seawinds data in its operational variational data assimilation scheme. As with other scatterometers, the observations contain a directional ambiguity and we resolve this directly in the data assimilation scheme through a cost function which contains a term for all wind ambiguities associated with an observation. Two month-long trials were performed using the Met Office global NWP system in order to assess the forecast benefit of assimilating this new data source to form analyses. The resulting forecasts were verified against in situ and satellite observations and a positive benefit was observed, particularly for short-range forecasts of sea level pressure. The impact of scatterometer winds on a forecast of a tropical cyclone was also investigated with encouraging results.

1. Introduction

In recent years satellite observations of near-surface winds over the ocean have become well used in operational Numerical Weather Prediction (NWP) analyses. This significantly increases the number of observations made over the open ocean, as conventional reports are generally restricted to coastal locations and shipping lanes. Both passive and active measurements in the microwave region can be used to infer near-surface wind information, allowing observations to be made in cloudy regions and, depending on the choice of wavelength, low levels of precipitation. In this study we will concentrate on the use of the Seawinds Ku-band scatterometer which has flown in space since mid-1999 on the single-instrument platform *QuikSCAT.* As with other scatterometer systems the wind vector over a patch of ocean is estimated from a set of backscatter measurements which view the scene at differing azimuthal angles. For centimetre radar waves the dominant backscatter mechanism is Bragg scattering off small-scale ocean waves. These in turn are driven predominantly by the local near-surface wind and consequently a relationship is expected between the scatterometer measurements and the wind. Ulaby et al. (1986) gives a fuller account of the process. Various models have been developed to describe the observed backscatter as a function of windspeed and direction and to date these have largely been empirically based. Backscatter models for Ku-band frequencies include those proposed by Jones et al. (1977) and Wentz et al. (1999). An important feature of ocean backscatter is that for a given windspeed the backscatter measurement is very similar if the wave field is rotated by 180° and is expressed within the backscatter models as a cosine dependence on the azimuth angle between the wind direction and the direction of the radar beam. This cosine dependence leads to retrievals producing multiple wind vector solutions for a given

set of backscatter measurements made over the same patch of ocean. There can be two or more of these wind solutions (referred to as ambiguities), each with similar windspeeds, but varying directions. Consequently an important issue for scatterometer assimilation in NWP models is how to deal with this directional ambiguity.

At the Met Office operational assimilation of scatterometer data commenced in 1994 with observations from the C-band Active Microwave Instrument (AMI) onboard *ERS-1* and *ERS-2*. For these instruments the wind ambiguity is principally two-fold, with the winds pointing roughly 180° apart (Stoffelen & Anderson (1997a) discuss the AMI inversion problem in detail). Ambiguity removal was performed prior to assimilation using a spatial filter (Offiler 1987) and pre-operational impact trials demonstrated an improvement in forecast skill, in particular for Southern Hemisphere sea level pressure (Andrews & Bell 1998). At the European Centre for Medium-Range Weather Forecasts (ECMWF) a different approach was adopted for using AMI data operationally. A dual-wind cost function was developed by Stoffelen & Anderson (1997b) as part of the variational assimilation scheme in operation at that centre. This approach has also demonstrated a positive impact on the resulting analyses, in particular for forecasting the movement of tropical cyclones (Isaksen & Stoffelen 2000). One of the main benefits of moving to variational ambiguity removal is that the amount of pre-processing before scatterometer data can be assimilated is reduced, as all the likely wind vectors are supplied directly to the analysis scheme. Also the general nature of a scatterometer cost function is attractive as new observation types, such as Seawinds observations, can be implemented in a straightforward way.

Recently at the Met Office we have implemented and tested a scatterometer cost function for AMI observations that is similar in nature to ECMWF's (Candy 2001). This paper describes our initial use of observations from the Seawinds scatterometer using an updated

version of this cost function. Additionally we examine several issues regarding quality control of these data. Firstly, as Seawinds uses two circular scans, the number of beams sampling each patch of ocean together with the range of azimuthal angles varies along the swath. This causes the retrieved winds to have different characteristics (such as accuracy and number of ambiguities) along the swath. Secondly, backscatter measurements from existing Ku-band instruments are affected by rain droplets in the field of view and Seawinds data also has this problem to some degree.

This paper is structured as follows. Section 2 briefly describes the Seawinds data received at the Met Office and examines the extent of rain contamination in the wind retrievals. In Section 3 the form of the scatterometer cost function is described. Results of the impact of Seawinds data on global model analyses and forecasts are discussed in Section 4.

2. Seawinds Observations

a. Pre-processing to Wind Vectors

For operational applications we are interested in near-real time processing of Seawinds data and Leidner et al. (2000) gives information about the instrument and the processing of the observations performed at NOAA/NESDIS. Briefly, Seawinds uses a conical scanning antenna to emit two narrow beams of radiation in a circular pattern at the earth's surface. The resulting backscatter measurements (expressed as normalised radar cross section, symbol σ^o) are geolocated into nodes of size 25 km resulting in 76 nodes across the outer swath. The size of the complete swath is 1800 km and allows coverage of 90% of the earth's surface in 1 day. Winds are retrieved from the σ^os at NOAA/NESDIS using a backscatter model similar to Wentz & Smith (1999). This is performed for each node over the ocean and

between two and four directional ambiguities can be found per node. For a particular observation the ambiguities are ranked on the fit between the σ^os and the backscatter (forward) model. The Rank1 solution is the wind vector yielding the best fit and it is expected to have the highest probability of being the true wind vector. Both the σ^os and the ranked wind ambiguities are then passed to the Met Office and other NWP centres along with additional information regarding the quality of the retrieval. For further information on the format see Leidner et al. (2000). The main forecast runs at the Met Office have a data cutoff of two hours and forty minutes after run time and so swift dissemination of the observations is essential for operational use. The arrival time of Seawinds data has been routinely monitored at the Met Office and we find that on average 95% of the data arrive within three hours, allowing an appreciable amount of Seawinds data to be used in forming the operational analyses.

b. Rain Contamination and Data Quality

Previous work has provided evidence on how rain can contaminate measurements from Ku-band instruments. For example, Guymer et al. (1995) looked at altimeter observations and noted that the main effect was attenuation if rain bands were present in the field of view. Figa and Stoffelen (2000) focused on the effect of rain on retrieved windspeeds from the NASA Scatterometer (NSCAT). They found that the fit between NWP model winds and those from the scatterometer was much poorer in the presence of rain than in non-raining conditions. Prior to assimilation studies with Seawinds data we have looked for similar contamination in this new scatterometer dataset. In a similar manner to Figa & Stoffelen one week of Seawinds data were collocated with windspeed estimates from an NWP model and Special Sensor Microwave Imager (SSM/I) observations (in the form of brightness

temperatures). For our study model windspeeds came from the operational Met Office global NWP model analyses and represent the wind at a height of 10 m above the ocean. The SSM/I observations were used to determine whether it was raining at each matchup location using the rain rate algorithm from Ferraro et al. (1995). The collocations were then split into two subsets; one in which no precipitation was detected and one in which precipitation was present (according to the SSM/I rain estimates). We focused on the inner beam region of the swath as it is here that more accurate wind retrievals are expected, due to the four radar looks at the ocean, compared to two looks in the outer regions of the swath. Comparisons between the model and scatterometer winds for these two subsets can be seen in Figure 1. Figure 1(a) presents all the matchups and it can be seen that above 15 m s^{-1} a large proportion of the scatterometer windspeeds are greater in magnitude than the NWP estimates. This is also reflected in the mean bias between the two observation types at high windspeed. In Figure 1(b) which contains the matchups where no rain was present (according to SSM/I) the fit has improved, though a small positive bias still remains at high windspeed. Rain contamination therefore also degrades Seawinds observations in a similar manner to other Ku-band radars and the major effect is to add a positive bias to the retrieved wind. These findings are consistent with studies performed elsewhere (e.g. Stiles & Yueh 2002). Detection of such observations contaminated by rain is important to ensure they are rejected prior to assimilation and a method to do this will be discussed in the next section.

c. Quality Control

There are several ways in which scatterometer data can be screened for rain. The data could be collocated to SSM/I or NWP model estimates of rainfall. These approaches would require close matchups in space and time to ensure that rapidly changing rain events

are correctly captured. A more attractive approach is to use the scatterometer observations themselves to diagnose the presence of rain in the field of view. Figa & Stoffelen did this successfully for the NSCAT scatterometer (which operated at a similar frequency to Seawinds) in the following way. As mentioned earlier the process of wind retrieval involves the comparison between the backscatter measurements, σ^o, and a forward model, f, which describes how the backscatter varies with incidence angle, θ, surface windspeed, U, and relative wind direction to the beam, φ. The method generally used to do this involves maximising a function, R, known as a maximum likelihood estimator (MLE). It contains a term for each backscatter observation made over the patch of ocean of interest (JPL 2000).

$$R = -\sum_{i=1}^{N} \frac{(\sigma_i^o - f(U, \theta_i, \varphi_i))^2}{\mathrm{SD}_i^2} \qquad (1)$$

Where SD represents the expected scatter of the observations about the model surface, as a standard deviation, and contains contributions from the accuracy of the measurement and the forward model prediction. N represents the number of backscatter measurements made within a node of interest, which is normally 4 for the inner beam region of the Seawinds swath. Figa & Stoffelen suggest that the value of R for the Rank1 (or best fit) wind solution, R_1, can act as a useful quality indicator. Large values of R_1 suggest a poor fit between the forward model and the observations, indicating that other geophysical effects are starting to influence the signal, in addition to the wind-driven roughness. Although Figa & Stoffelen concentrated on NSCAT, the method is also applicable to Seawinds data as we demonstrate below.

Values of R_1 are provided by NOAA/NESDIS as part of the observation record and these were examined for all Seawinds wind retrievals in the inner beam. A residual trend

was observed with windspeed and was removed using an empirical fit. Following the convention used in the NSCAT work we use the following transformation of R_1 to form a retrieval quality indicator:

$$QI = \sqrt{|R_1|} \qquad (2)$$

From the Seawinds collocations with SSM/I (mentioned in the previous section) we computed a histogram of QI for the rain free subset and the raining subset and these are compared in Figure 2. Higher values of QI are associated with the rain dataset and above a value of 1.8 the rain dataset has a significantly higher number of observations in each histogram bin. We therefore use this threshold as an indicator of the presence of rain in the field of view. It is encouraging to note that Figa & Stoffelen arrived at the same threshold for NSCAT using comparisons with NWP model data.

Typically about 6 % of Seawinds data are rejected by this retrieval quality test. The global distribution of rejections is shown in Figure 3, using 18 days of data from December 2001. The figure demonstrates that most of the rejections are associated with rain and in particular regions of tropical convection such as the Tropical West Pacific and Tropical Indian Ocean. In contrast, areas associated with little precipitation, such as the sub-tropical highs, have very few observations rejected. The retrieval quality test should also reject observations inconsistent with those expected from a wind-roughened sea and in Figure 3 evidence can also be seen of rejection due to ice contamination. Two examples of this are on the ice edge around Antarctica and in the Caspian Sea. A rain flag is also supplied with each observation as part of the processing at NOAA/NESDIS. It uses several properties of the observations known to be sensitive to rain and more details can be found in JPL (2000). We use this

information as an additional test, rejecting observations from use in the analysis if either the supplied rain flag or the QI test indicates rain.

d. Bias correction of Seawinds wind speeds

The data assimilation process is particularly sensitive to biases between observed and modelled data. It is therefore preferable to eliminate biases in some way. Seawinds data have been monitored at the Met Office and results have shown typical mean biases of ~0.6m/s between the observed winds and those from the Met Office six hour forecasts. The wind speed bias is observed to be non-linear with wind speed and so we choose to perform a wind speed dependent bias correction (figure 4). This is done using the following formula and is valid for windspeeds up to 40 m/s:

$$U_{new}=bc_1+bc_2U_{old}+bc_3U_{old}^2+bc_4U_{old}^3 \qquad (3)$$

Here, U_{new} is the bias-corrected wind speed, U_{old} is the original wind speed and bc_i (i=1-4) are coefficients determined by performing a cubic polynomial fit to the observed and modelled data. The bc_i coefficients have been periodically recomputed to adapt to changes in the error characteristics of both Seawinds and the Met Office global model. Note that in this scheme the wind directions are completely conserved.

3. Data Assimilation

Met Office global analyses are formed using a four-dimensional variational scheme (4D-Var as described by Rawlins et al. (2006)). In this section we discuss how scatterometer data are incorporated into the assimilation scheme. The resolution of the analysis grid is approximately 100km, which is significantly coarser than the Seawinds observations (25km).

Consequently the scatterometer observations will contain smaller-scale structures than the NWP model can resolve, potentially leading to poor fitting of the data in the resulting analyses (Stoffelen 2000). Additionally within the 4D-Var scheme observations are assumed to be independent. However neighbouring Seawinds observations are likely to have correlated errors (e.g. in the vicinity of a rainband). As with other sources of data that have a higher resolution than the model (e.g. satellite radiances, *ERS* scatterometer winds) data thinning is used to surmount these difficulties. A thinning level of 1 observation per analysis gridpoint was used in AMI assimilation and we repeat this for Seawinds, which amounts to a thinning of roughly 1 in 16 observations. Stoffelen suggests that, instead of thinning, a better approach is to retain all the information by averaging the backscatter observations down to the resolution of the analysis grid. Wind vectors are then retrieved at the coarser resolution. This would lengthen the processing required at the Met Office which is undesirable for operational use, though it may be investigated in the future to assess the potential benefit.

The Met Office 4D-Var assimilation scheme forms an analysis by combining information from a previous short-range NWP forecast (often termed the background) and recent observations. Within the variational method this is achieved by finding, through successive iterations, the atmospheric state which minimises a cost function, *J*. *J* consists of a background term and a term containing contributions from observations and so to incorporate Seawinds observations we need to specify an appropriate observation cost function. Lorenc (1988) discusses how a cost function is formed for an observation type from knowledge of its error characteristics. Typically a Gaussian error distribution is assumed, leading to a quadratic observation cost function for a single observation of the following form:

$$J^o = \frac{(\mathbf{y} - \mathbf{H}(\mathbf{x}))^2}{2\varepsilon^2} \quad (4)$$

where $\mathbf{y}$ represents the observation and **H** represents the operator that transforms the analysis state $\mathbf{x}$ into a model equivalent of the observation. The observation error is denoted by ε and contributions to it arise from both instrumental errors and representativity errors inherent in the NWP model. For the case of scatterometer observations there is a choice in how to form the cost function (Equation 4). It could either be formed in the measurement space, i.e. $\mathbf{y}$ represents the radar observations and **H** includes the backscatter model, or in the model space. In this latter choice $\mathbf{y}$ represents the retrieved (ambiguous) wind solutions and **H** represents an interpolation of the surface model wind field to the observation location. Stoffelen & Anderson (1997b) and Stoffelen (2000) discuss these two approaches and conclude that using the retrieved winds is preferable because the dominant source of observation error is the representativity error from the atmospheric model. Whilst this error source tends to be Gaussian in model space, it will form non-Gaussian error statistics in the measurement space, due to the inclusion of a non-linear backscatter model within the operator **H**. We follow this suggested strategy and in forming the scatterometer cost function start by considering a scatterometer observation as consisting of *N* wind vectors, u^o_i,v^o_i, each with a prior probability P_i^o of being the true wind solution. The observation may be grossly erroneous in which case none of the winds represent the true wind and this can be represented by a flat error distribution (Lorenc & Hammond 1988). So the scatterometer observation error distribution is modelled using a combination of Gaussian functions and a flat distribution, which leads to the following cost function:

$$J^o_{scat} = -\ln\left(\sum_{i=1}^{N} P_i^o e^{-j_i} + P_g 2\pi\varepsilon^2 k\right) \quad (5)$$

where

$$j_i = \frac{(u - u_i^o)^2 + (v - v_i^o)^2}{2\varepsilon^2} \quad (6)$$

and ε represents the observation error. The probability of gross error is represented by P_g, whilst k is a constant representing a gross error distribution over a large but finite range of width $k^{-0.5}$ in u and v. For the assimilation experiments detailed later the values of k, P_g and ε were set to 0.0015 m^{-2} s^2, 0.02 and 2 m s^{-1} respectively. The prior probabilities P_i^o control the relative depth of each minima within J_{scat}^o and are normalised so that $\sum_{i=1}^{N} P_i^o = 1 - P_g$. These prior probabilities have been empirically determined for Seawinds by comparing which ambiguity was the closest to the corresponding Met Office wind analyses (formed without using Seawinds data) and then deriving probabilities from a large number of comparisons. In practice it is found that the Seawinds wind retrievals have good directional skill, i.e. the Rank 1 ambiguity is the most likely to represent the correct wind direction, according to the analyses. The skill is greater for higher windspeeds and as the value of the Rank1 MLE becomes smaller relative to the other ambiguities. Accordingly simple predictors for P_i^o have been determined based on these statistics. Seawinds retrievals can contain up to four ambiguous winds per observation and so in practice the cost function (Equation 5) can contain up to four minima. By contrast ECMWF use a dual-wind scatterometer cost function regardless of the number of ambiguities present (Hersbach et al. 2003). Each minimum has equal depth, with the consequence that the directional skill inherent in Seawinds observations is ignored.

Taking into account the likelihood of gross error within the cost function allows for quality control within the variational analysis procedure and the method followed is similar to

that described by Andersson & Järvinen (1999). Initially P_g is set to zero and so all scatterometer observations can influence the analysis. After about half the iterations in the variational process P_g is increased above zero. With the consequence that any observations far from the latest atmospheric state play no further part in influencing the analysis as in these cases the contribution to the gradient of the observation cost function is now zero.

4. Forecast Impact Trials

a. Introduction

It is normal practice at the Met Office to assess the impact of a new observation type on NWP forecasts relative to the current operational NWP system and in this section we describe how trials were performed for Seawinds data. The Met Office operational NWP system generates a global analysis every six hours (at 0, 6, 12 & 18 UTC) using the 4D-Var scheme described by Rawlins et al. (2006). From each analysis the Met Office atmospheric model generates a six hour forecast to provide a background for the next analysis and at 0 and 12 UTC this is extended to produce global forecasts out to five days. The atmospheric model was originally introduced over ten years ago (Cullen 1993) and since then has been regularly enhanced, with the version used in the current work containing a non-hydrostatic dynamical core (Davies et al. 2005). For the Seawinds impact trials the control run of the NWP system was closely based on the operational suite, with the notable exceptions that the forecasts were run at a resolution of approximately 100 km and the analyses were formed using a 3D-Var scheme. This is half the operational resolution and was chosen in order to reduce computational time. Observations used in the control run are described in Table 1. The main source of marine wind information comes from the SSM/I instruments in the form of retrieved windspeed, with a smaller number of in situ wind reports from ships and

buoys. In the experiment run Seawinds data were also included in the 3D-Var scheme, via the scatterometer cost function (Equation 5). In addition to the quality control and thinning described earlier, only observations from the mid regions of the inner beam were used (Nodes 12-28 and 49-65). This resulted in around 8000 additional observations in any six-hour cycle and almost doubled the marine wind data being used in the assimilation scheme. Control and experiment runs were performed for two four-week periods, commencing 21 June 2001 and commencing 25 September 2001. Differences between the experiment and control forecasts are discussed below for these two periods, however an initial look at the effect of the Seawinds observations can be made by comparing the analysis increments (expressed as rms differences between the analyses and the corresponding backgrounds). An example of this is shown in Figure 5 for the June trial in the form of a zonal mean difference between the experiment and control increments of the u-wind component. The differences are largest in the Southern Ocean, and so it is here that we expect the biggest forecast impact from Seawinds observations. Differences are also apparent in a small zone in the equatorial Tropics. The distribution of changes to the increment field is similar if plotted for runs made in a different season (not shown). Figure 5 also demonstrates a further aspect of the variational assimilation system. The wind information from the scatterometer is presented to the analysis at the surface. Changes can be observed at this level and also higher into the free atmosphere as the information is propagated aloft through the vertical structure of the background error covariances used within the 3D-Var scheme.

b. Fit of the background fields to observations

A useful diagnostic from the assimilation system is the rms difference between the background field (a six-hour forecast) and the next set of observations. Table 2 compares

these rms differences for both control and experiment runs for the two trials. Observation types shown are those most likely to be sensitive to a change in quality of the surface wind forecasts. For each trial the change in the rms difference, expressed as a percentage, is displayed. For each observation type the change is either zero or positive, with a positive change signifying that the fit of the background to the observation type has improved when Seawinds data are used to form the analysis. Large improvements are seen in the fit of the background to altimeter observations of surface windspeed. This is particularly encouraging because the altimeter data (from the *ERS-2* satellite) are not used in the trials and so can be considered as an independent set of ocean wind measurements.

c. Impact on NWP forecasts

The quality of the forecasts derived from the control and experiment analyses for both trials were objectively assessed by calculating forecast differences from observations. For a particular parameter of interest this was done by comparing each forecast in the trial period with observations valid at the time of the forecast and then deriving the rms difference between the observation and the forecast. These differences were derived for sea level pressure using reports from marine and land stations as the verifying observations, whilst sonde observations were used to verify forecasts of 850 hPa windspeeds and geopotential heights at 500 hPa. The impact on the near-surface forecasts is presented for three latitude bands in Figure 6. The bands consist of the Northern Hemisphere and Southern Hemisphere Extratropics (in each case areas poleward of 30˚) and the Tropics (30˚S to 30˚N). The forecast-observation rms differences are presented as the percentage change between the control and experiment run, with positive changes indicating improvements in forecast accuracy due to the inclusion of Seawinds. The majority of the surface forecasts have been

improved, with the largest changes in the Southern Hemisphere Extratropics, and in particular for the June trial out to 72 hours (3 days). Much smaller improvements are observed in the Tropics and this is consistent with results from previous trials using other scatterometers (e.g. Candy 2001). Although the tropical signal is small this has been derived for results over a large spatial region and so important localised impacts may well be hidden. We examine this in the next section by looking at a tropical cyclone case study. Positive impacts are also observed in the 500 hPa height field for both extra-tropical regions, with again larger impacts in the Southern Hemisphere (Figure 7).

d. A tropical cyclone case study

At C-band the contamination of the ocean backscatter signal due to clouds and rain is small and so scatterometers operating in this frequency range can provide detailed information on the surface wind field of tropical cyclones. As most cyclones develop in the open ocean, far from shipping lanes or buoy networks these satellite observations have an important role in improving the representation of tropical cyclones in NWP analyses and subsequent forecasts of their tracks. At ECMWF the impact of the AMI instrument in 4D-Var was assessed for an active period during the Atlantic hurricane season in 1995 (Isaksen & Stoffelen 2000). The scatterometer improved the hurricane track forecasts (out to five days) in the majority of cases. For Ku-band scatterometers the interaction with rain droplets becomes an important issue, particularly for the intense rainbands present around the eye of a fully developed tropical cyclone. In this frequency band a number of case studies again performed at ECMWF showed improvements in the track forecasts due to the inclusion of data from the NSCAT instrument (Leidner et al. 2003). We now investigate the effect of Seawinds data on the representation of a tropical cyclone within the Met Office model.

For this work a similar trial was performed as in the impact studies detailed earlier, except for this case study the forecast model was run at the full operational resolution in order to describe the structure of the cyclone in as much detail as possible. An important technique used within the Met Office operational assimilation system for representing tropical cyclones is to create synthetic or 'bogus' observations from the reported locations issued by hurricane monitoring centres (Heming et al. 1995). In order to investigate the full effect of the scatterometer data both the control and experiment run were performed with these bogus observations withdrawn. Instead the reported locations of the cyclone centre, many of which are determined from geostationary images, were used to verify the position of the cyclone in the analyses. The cyclone of interest was named Faxai and existed in the North West Pacific during the latter part of December 2001. Faxai attained tropical depression status on the 15 December and seven days later was classified as a Supertyphoon with reported winds in excess of 130 kt (65 m s^{-1}). Accordingly the trial runs were performed for eight days from the 16 December. During this period the inner beam of *QuikSCAT* made 12 passes over the cyclone and this information was assimilated into the experiment run. Using a similar method to Isaksen & Stoffelen (2000), the position of the cyclone in the control and experiment analyses was determined from the maxima in the relative vorticity field at 850 hPa and then compared to the reported location. For the twelve analyses of the experiment run in which Seawinds data were assimilated the mean positional error of the cyclone improved by 11 % over the control run, although if analyses are included in which there were no passes by Seawinds over Faxai then the improvement drops to 2 %. The largest improvement was observed on the analysis at 6 UTC on 17 December when Faxai had reached tropical storm intensity and the analyses are presented for this time in Figure 8. In the upper left panel of Figure 8 the Seawinds data presented to

the assimilation system are compared to the reported centre of the cyclone (marked by the letter A). The winds plotted are the Rank 1 retrievals and this demonstrates the directional skill of the wind retrieval since most of the vectors are pointing in the expected direction of cyclonic flow. The circulation from the winds appears consistent with the reported location, whilst at the centre of the cyclone observations are missing. This is most probably due to the rain screening tests. Nevertheless there are a large number of observations in the vicinity of the cyclone that can be used in the assimilation. In the upper right panel the background forecast is shown from the experiment run and it can be seen that the model forecast of the cyclone is close to the reported centre. The assimilation of the scatterometer winds has resulted in a stronger circulation and a closer fit between the reported cyclone centre and the model equivalent. To demonstrate that these improvements are due to the scatterometer data alone the final panel shows the control run representation of the cyclone and we see a weaker feature whose position is further from the reported centre. The improved cyclone positioning for this case is also carried forward in the resulting forecast out to 48 hours. These results are encouraging, although more cases from different cyclones need to be examined both in the analyses and forecasts to fully understand the impact of Seawinds on cyclone track prediction.

5. Conclusions

In this paper the initial implementation of Seawinds data within the Met Office assimilation scheme has been described. The observations arrive at the Met Office in the form of retrieved winds including the directional ambiguity and this greatly simplifies the pre-processing prior to assimilation. Quality control forms the main component of this pre-processing which is principally to reject rain contaminated data. For this task we have used

an existing MLE threshold test and applied it to Seawinds data. For those observations that pass quality control the directional ambiguity is presented to the assimilation system via a multiple wind cost function. These data roughly double the amount of near-surface marine observations used in the assimilation scheme and two months of impact studies using the Met Office global NWP system have demonstrated a positive benefit. This benefit is mainly for short-range forecasts of sea level pressure out to 72 hours and in particular over the Southern Hemisphere. These results are consistent with other impact studies using earlier scatterometer designs, e.g. *ERS-2* (Candy 2001) and Seawinds data (Hersbach et al. 2003). A case study of the representation of a tropical cyclone within model analyses has also been performed and suggests that the Seawinds data help to improve the positioning of such systems. Repeating this analysis for a set of cyclones would be very instructive and in particular a comparison of the relative benefit of scatterometer data versus our current operational method of positioning tropical cyclones in global analyses using bogus observations.

There are a number of developments that can be carried out to improve the use of Seawinds data in the system described here. We initially chose to use the regions of the inner beam of the swath where wind retrievals were anticipated to be the most accurate. One aspect of using Seawinds data that we have not addressed in this study is the disparity in resolution between the retrieved winds (25 km) and the analysis grid (roughly 100 km). Currently we thin the observations to 1 per analysis grid point. An alternative is to take the observations and process them in some way so that they represent the analysis resolution. Stoffelen (2000) has suggested spatially averaging the backscatter observations down to the analysis grid and then performing the wind retrieval at this new resolution. This approach could be tried at the Met Office, though it would complicate the processing required before

assimilation and necessitate the incorporation of a backscatter model. Nevertheless it would be a useful experiment to understand the effect of observation resolution on the resulting forecast impact.

The variational approach to handling the directional ambiguity inherent in scatterometer wind data has resulted in forecast benefit at other NWP centres and in this study we have shown it to be also useful in the Met Office model. The form of the cost function is likely to be used for the next generation C-band instrument ASCAT on *METOP* and could also be considered for other observation types in which a directional ambiguity is present such as the current *Windsat* passive microwave mission.

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Tables

TABLE 1. Existing observations used in the Seawinds impact trials.

Observation Type	No. Assimilated*
ATOVS radiances	14000
Wind Profilers	500
Radiosondes	500
Cloud track winds	6000
Aircraft reports	6000
SSM/I	8500
windspeeds**	5000
Land reports	2000
PMSL	
Ship & buoy PMSL	

*Typical number used in a 6-hour assimilation window.

**Over ocean only.

TABLE 2. A comparison of the RMS difference between observations and the six hour background forecast. Statistics for the two trials are shown.

Observation Type	**July 2001 Trial**			**September 2001 Trial**		
	RMS O-B			RMS O-B		
	CON	EXP	IMP	CON	EXP	IMP
Sonde winds* (m s^{-1})	4.15	4.15	0.1	3.82	3.82	0.0
Cloud track winds* (m s^{-1})	2.96	2.94	0.5	3.04	3.01	0.9
Aircraft winds* (m s^{-1})	3.87	3.87	0.0	4.16	4.16	0.1
Ship PMSL (mb)	1.22	1.22	0.1	1.28	1.28	0.5
Buoy PMSL (mb)	0.92	0.90	1.6	0.96	0.95	0.9
SSM/I windspeeds (m s^{-1})	0.76	0.74	2.3	0.73	0.71	2.4
Altimeter windspeeds (m s^{-1})	1.72	1.67	2.9	1.70	1.64	3.5

CON = RMS difference between observations and control backgrounds.

EXP = RMS difference between observations and experiment backgrounds.

IMP = Percentage difference of CON-EXP.

*Observations in the lower troposphere (1000-700 mb).

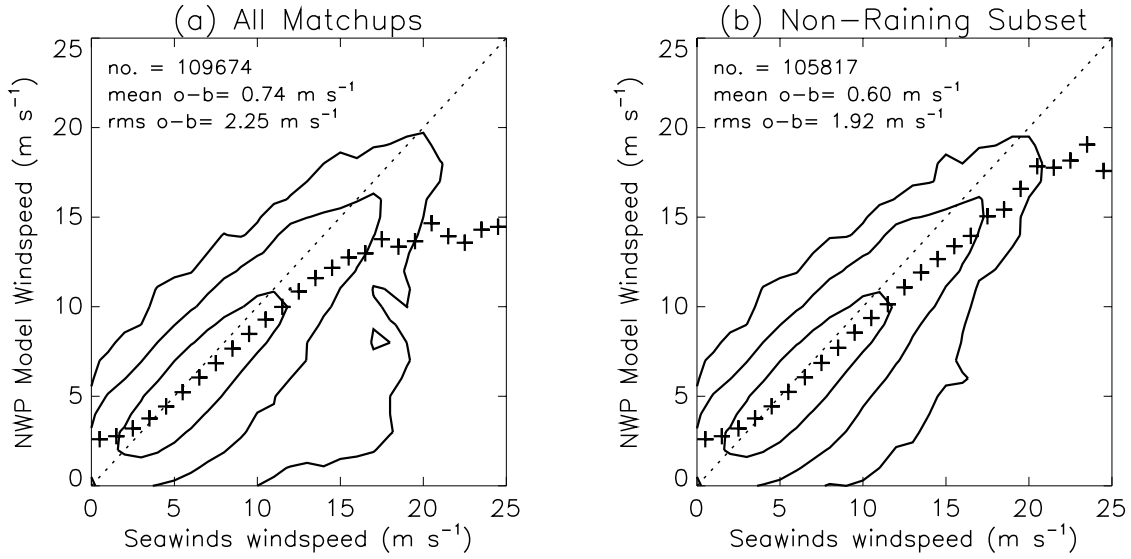

Figure 1. Comparisons between Seawinds observations of surface windspeed and the corresponding Met Office global model wind analysis at 10 m for (a) all matchups and (b) non-raining matchups. In each case contours indicate where the majority of data lies in steps of 10, 100 and 1000. Crosses represent the mean values.

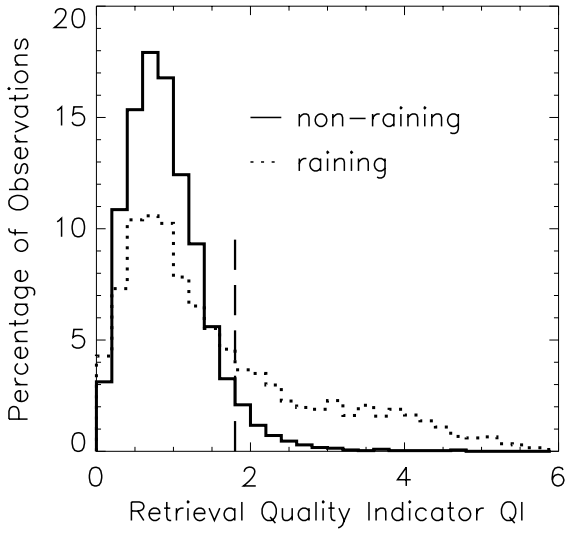

Figure 2. Use of the Seawinds retrieval quality indicator (QI) as a rain flag. The dotted line indicates the distribution of QI for retrievals with rain present (according to SSM/I) and the solid line for retrievals in the absence of rain. A dashed vertical line denotes the rain threshold derived from these distributions.

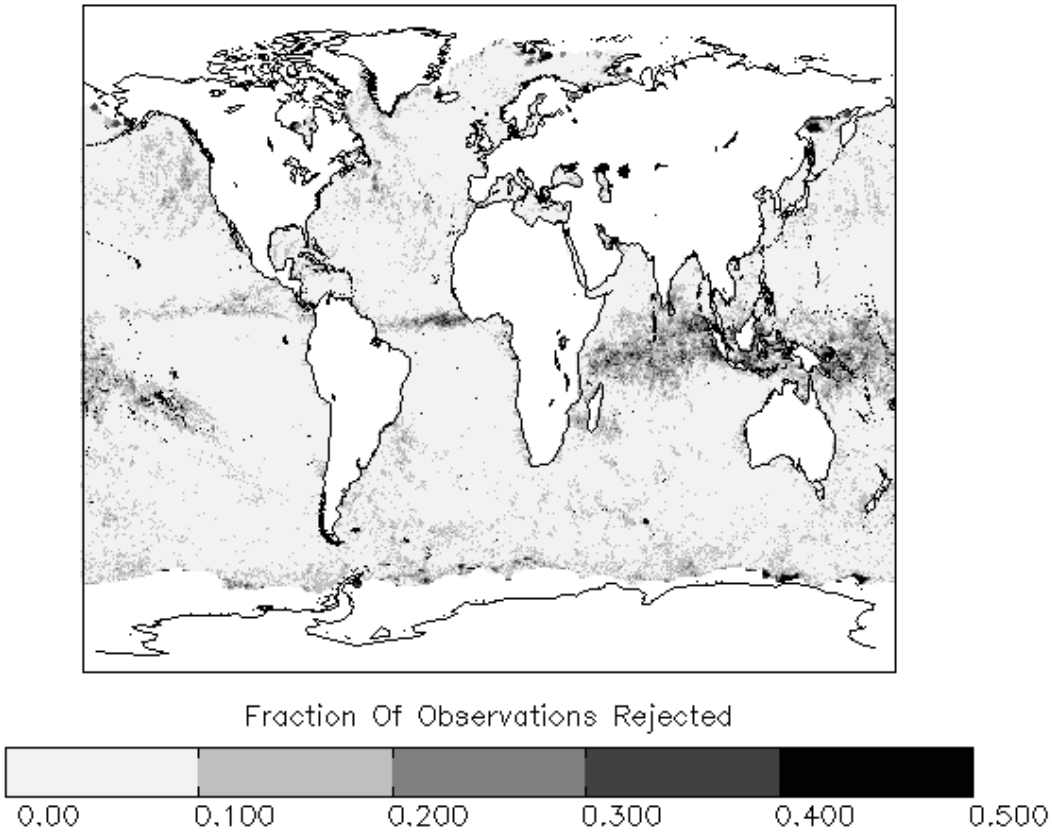

Figure 3. The fraction of Seawinds observations rejected by the QI test for 18 days in December 2001. All observations for which wind retrieval was possible have been used to form the plot.

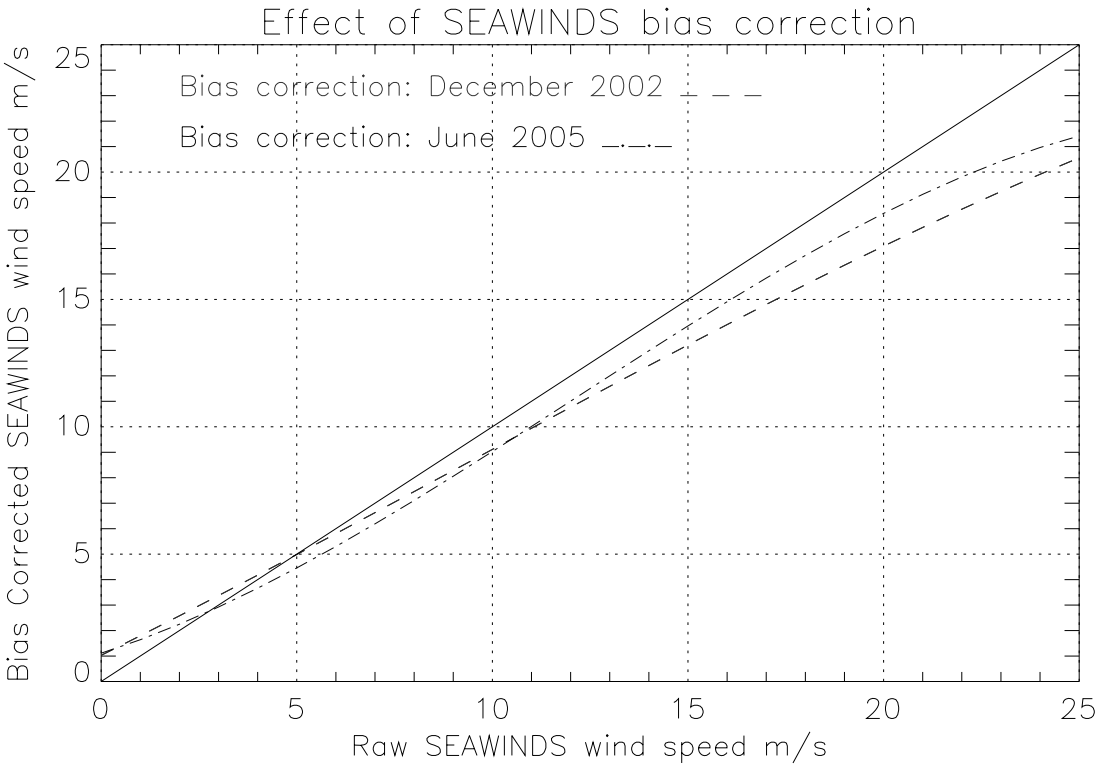

Figure 4. Bias correction of Seawinds on QuikSCAT platform. It is evident that the bias correction at the higher wind speeds is lower from the update in June 2005 than for December 2002. This may be due to model improvements e.g. improved model resolution leading to reduced representivity errors.

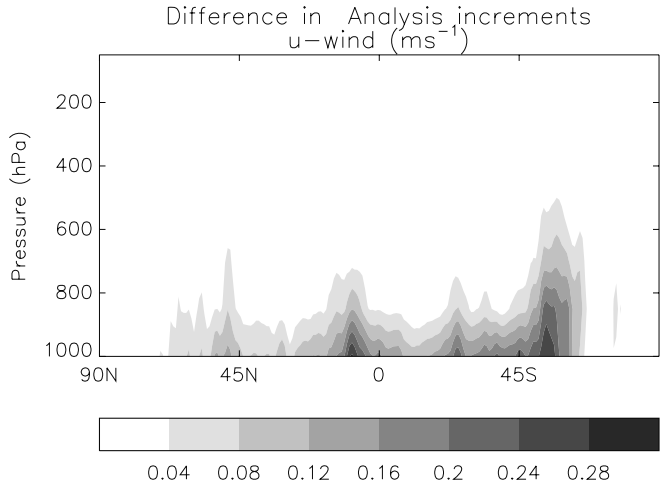

Figure 5. The zonal mean difference in u-wind rms analysis increments between the experiment runs (Seawinds included) and the control runs (Seawinds withheld). Data is taken from the July 2001 period and only model grid-points over the ocean are included.

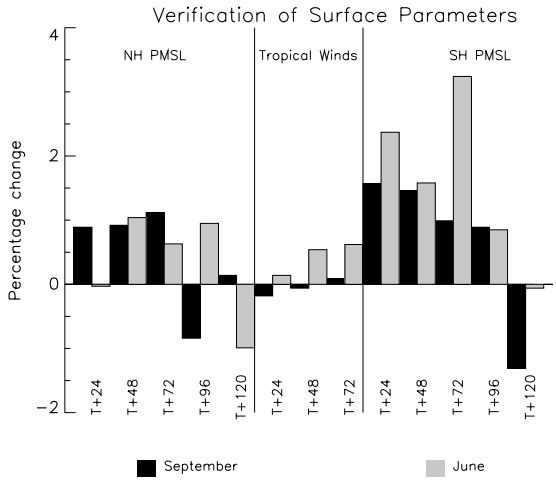

Figure 6. The percentage change in the forecast-observation rms difference between control and experiment runs for extratropical sea level pressure and tropical near-surface windspeeds. Both trial periods are shown, the June trial as light grey bars and the September trial as dark bars.

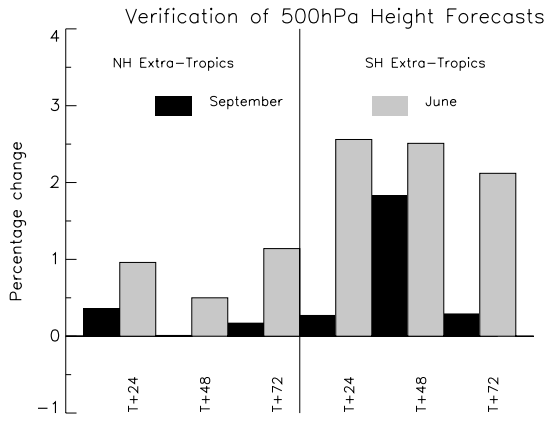

Figure 7. The percentage change in the forecast-observation rms difference between control and experiment runs for 500 hPa heights. June trial results are represented as grey bars and the September trial results as dark bars.

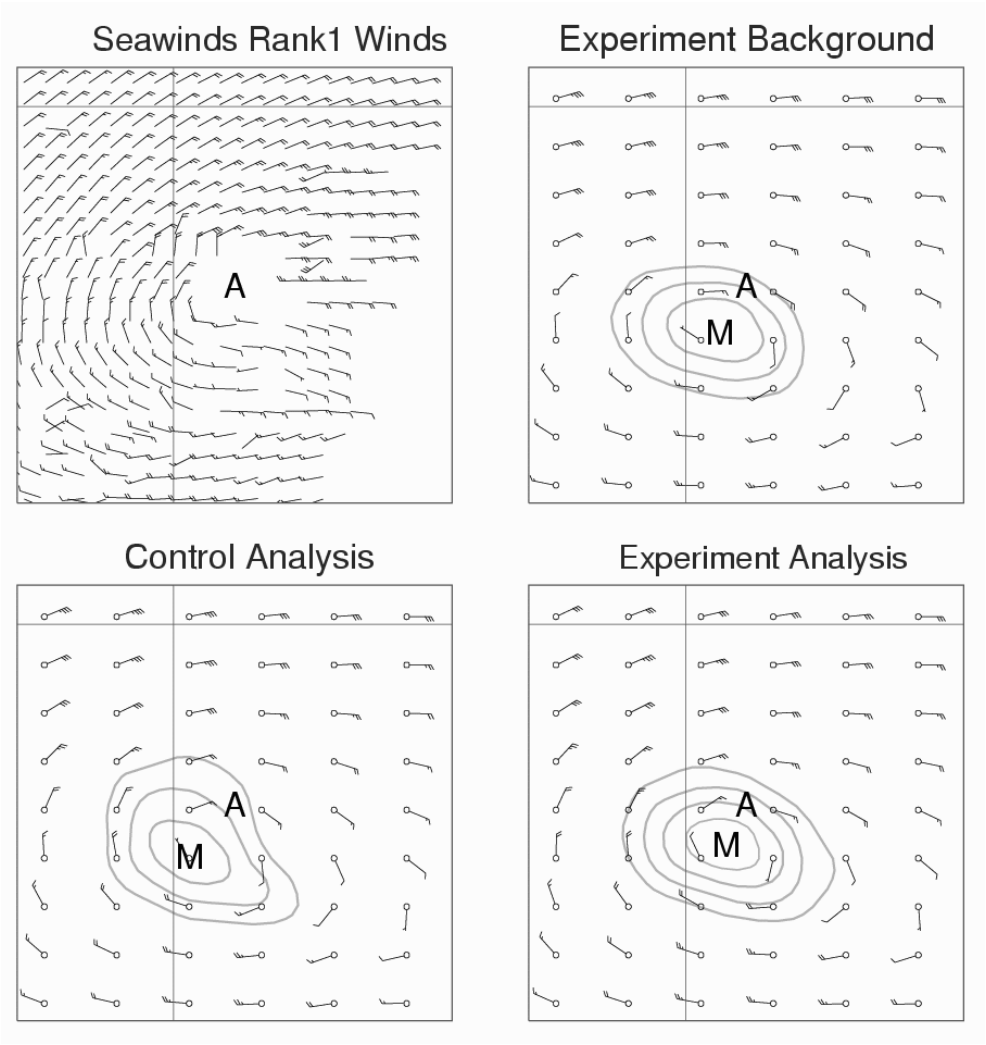

Figure 8. The representation of Tropical Storm Faxai in the Met Office model for the analysis of 17 December 2001 at 6 UTC. The Rank 1 wind retrievals assimilated are shown in the top left panel. The background forecast from the experiment (Seawinds assimilated) run is shown in the top right, whilst the resulting analysis is shown in the bottom right panel. The corresponding control analysis is shown for comparison in the bottom left panel. In each case M represents the model location of the storm and A the reported centre. Windspeeds are in knots and contours represent the relative vorticity field at 850 hPa (minimum value $6x10^{-5}$ s^{-1}, interval $2x10^{-5}$ s^{-1}).